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Determining the Optimal Spatial Resolution of Remotely Sensed Data for the Detection of *Sirex Noctilio* Infestations in Pine Plantations in KwaZulu-Natal, South Africa

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ABSTRACT

Sirex noctilio is causing considerable mortality in commercial pine plantations in KwaZulu-Natal, South Africa. The ability to remotely detect variable (for example, low, medium and high) *S.noctilio* infestation levels remains crucial for monitoring of the actual spread of the disease and for the effective deployment of suppression activities. Although high resolution image data can detect and monitor *S.noctilio* infestations there are no guidelines to the appropriate spatial resolutions that are suitable for detection and monitoring purposes. This study examines the use of minimum variance to analyze *S.noctilio* infestations in an effort to determine an optimal spatial resolution of remotely sensed data for forest health monitoring purposes. High resolution (0.5 m) image data was collected using a four band airborne sensor and infestation levels were derived using the normalized difference vegetation index (NDVI) and Gaussian maximum likelihood classifier. It was determined that the appropriate spatial resolution for the detection and monitoring of S.noctilio infestations as estimated by the minimum variance of sub samples narrowly differed based on the level of localized infestations present in the study area. Pixel sizes larger than 2.3 m will not provide adequate information for high infestation levels, while using pixel sizes smaller than the 1.75 m for detecting low to medium infestation levels will yield inappropriate results. The results of this study establish the necessary spatial resolution guidelines needed for the operational detection and monitoring of *S.noctilio*.

Introduction

In its natural habitat, the Eurasian woodwasp, Sirex noctilio typically attacks stressed pine trees (Neumann et al., 1981). However, as population levels increase, the wasp spreads through mature pine compartments and causes extensive mortality of larger trees (Haugen 2000, Ciesla 2003). S.noctilio infestation levels have reached epidemic proportions in KwaZulu-Natal, South Africa, with thirty percent or more of *Pinus patula* trees being killed in some plantations (Slippers 2006). In an effort to minimize the economic threat to commercial forestry, management strategies that combine the use of remote sensing, silvicultural treatments and biological control are currently being implemented (Ismail et al., 2005). The ability to remotely detect variable (for example, low, medium and high) *S.noctilio* infestation levels remains crucial for the monitoring of the actual spread of the disease and for the effective deployment of suppression activities (Ismail et al., 2006). For example, the ability to remotely detect light to medium *S.noctilio* infestations is beneficial because it allows forest managers to adopt a proactive course of remediation (for example, nematode inoculations) before the entire plantation reaches a point of non-recovery. However, it is unrealistic to expect that a single remotely sensed data source will be both sufficiently detailed and suitably cost effective to capture variable infestation levels at a compartment, or even at a broader plantation scale.

The availability and accessibility of airborne sensors (for example, ArcEagle, LReye and Geospace) in South Africa has resulted in the increased acquisition of remotely sensed image data. However, as an increasing number of remotely sensed datasets become commercially available the factor of spatial resolution plays an important role in the employment of remotely sensed image data (Quattrochi et al., 1997). Spatial resolution is defined as the limit on how small an object on the earth's surface can be 'seen' by a sensor (for example, 2.4 m pixel for QuickBird and 4 m for IKONOS) as being separate from its surroundings (Lillesand et al., 2004) and the basic information and measurement error contained in a remotely sensed image is strongly dependant on that spatial resolution (Woodcock et al., 1987, Atkinson, 1993). For current *S.noctilio* detection and monitoring purposes, forestry companies tend to use the finest resolution (0.5 m) available. However, using remotely sensed data with spatial resolutions finer than the structure of the vegetation community may introduce irrelevant variation and result in large data volumes and unnecessary cost (Menges et al., 2001). Methods need to be developed where each object under investigation can be considered at its 'optimal' spatial resolution (Marceau et al., 1994), where the information content per pixel is maximized (Atkinson, 1997). Additionally, for remote sensing of forest ecosystems to become operational, spatial resolutions of remotely sensed image data must be appropriate for the specific application (Treitz et al., 2000) and the data should be used with caution because of the potential problems that may arise from mismatches in scale between sensor and the practical requirements of the mapping exercise (Menges et al., 2001). The question then arises: on what basis should the investigator select an appropriate spatial resolution for the detection and monitoring of *S.noctilio* infestations?

Previous research (Woodcock et al., 1987; Atkinson, 1993, 1997, Atkinson et al. 2004) has shown that the spatial variation between objects in a scene can be used to select an 'optimal' spatial resolution and method of analysis for a given investigation. In forest environments, this relationship between the spatial variation in the objects of interest and spatial resolution has been described using average local variance (Woodcock et al., 1987), semivariance (Treitz et al., 2000, Colombo et al., 2004), minimal variance (Marceau et al., 1994, Menges et al., 2001) and spatial autocorrelation (Hyppanen, 1996). According to Marceau et al. (1994) the merit of using a minimal variance approach is that it considers different forest classes (for example, infestation levels) as opposed to an entire forest scene, thus making it a more suited indicator of the 'optimal' spatial resolution for each particular class under investigation. Minimal variance is based on the assumption that when a pixel representing an object of interest is considerably larger (L-resolution) or smaller (H-resolution) than the object, the probability of selecting pixels across the image with different digital number (DN) values is high and this leads to a high variance (Marceau et al., 1994). However, when the pixel of the image data delineates the appropriate mixture of ground features composing the object under investigation, the variance is then at the lowest level (information content is maximized) and can be used as an indicator of the 'optimal' spatial resolution required for the investigation (Marceau et al., 1994).

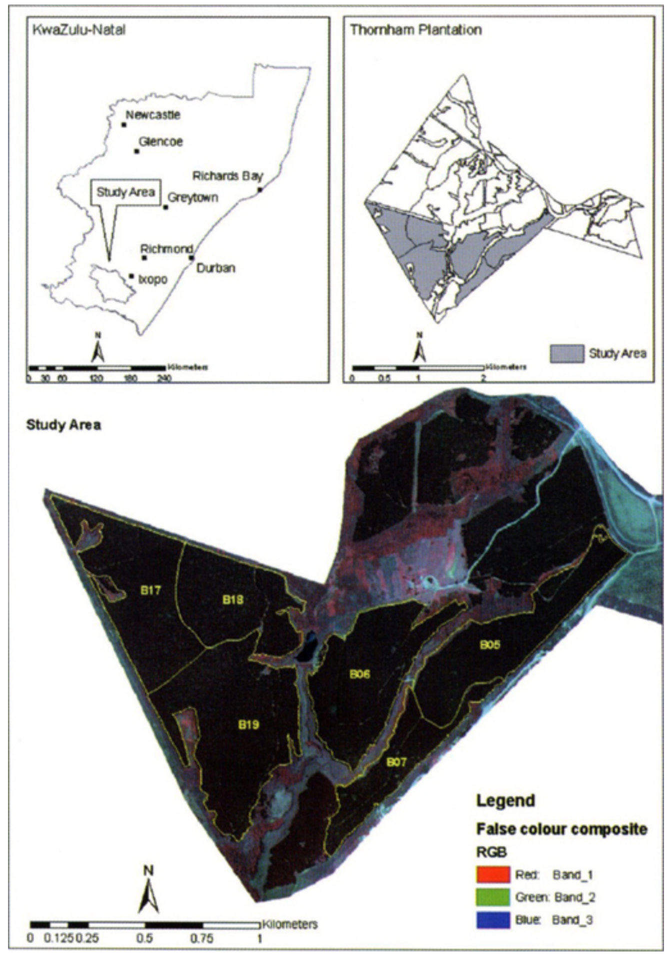
As part of a larger research effort aimed at reducing the effects of *S.noctilio* on pine production patterns in KwaZulu-Natal, Ismail et al. (2006) showed that high resolution image data can be used to detect and monitor *S.noctilio* infestations. However, there was no guideline to the appropriate spatial resolutions that are suitable for detection and monitoring purposes. This study aims to extend the work of Ismail et al. (2006) by using the minimal variance of classified NDVI images to define appropriate pixel sizes to capture the spatial variability of *S.noctilio* infestations. By establishing the spatial limitations of image data under variable infestation levels, we hope to contribute useful information and provide the necessary guidelines for the operational detection and monitoring of *S.noctilio* at compartment or plantation scales.

Methods and materials

Study area

The study area is part of the Mondi Thornham plantation (Figure 1) and is situated in the Midlands area of KwaZulu-Natal. The area lies at an altitude of 1,500 m above sea level with frost occurring in most areas between May and September (Schulze et al. 1997). Rainfall varies between 800 mm and 1200 mm per year, with high rainfall experienced predominately during the mid-summer months (Schulze et al., 1997). Lithology is predominantly shale, and to a lesser extent dolerite. Soils are characterized by fine sandy clay, humic topsoil, underlain by yellow or red apedal subsoil. Dominant soil forms are Inanda and Magwa. Clay contents vary between 25 % and 35 % in topsoil horizons and attain values of up to 45 % in subsoil horizons (Schulze et al., 1997).

Figure 1: Location of the study area. Image data shown is a false colour composite consisting of the NIR, red and green bands. Compartments selected for the study are indicated in yellow.



Sirex noctilio infestations

As part of the detection and monitoring framework used by the forestry industry, current *S.noctilio* infestations are determined by identifying the red stage of attack (Ismail et al., 2006). The red stage of attack occurs approximately three months after adult flight and oviposition, when the foliage of infested trees wilts and changes color from green to yellow to reddish brown (Haugen et al., 1990, Stone et al., 2004). Infestation levels are then categorized into the following damage classes: low (1-5%), medium (6-10%), high (11-15%) and severe (>16%) (Croft 2006). Similarly, in this study, infestation levels were calculated as the percentage of red stage trees to the total number of trees.

Table 1: Compartments selected for this study (n = 6).

Compartment	Age	Area	Species	Planted stems per ha (SPH)	Current stems per ha (SPH)
B05	16	21.5	*Pinus. patula*	1111	678
B06	16	22.8	*Pinus. patula*	1111	732
B07	16	11.8	*Pinus. patula*	1111	814
B17	16	23.7	*Pinus. patula*	1111	690
B18	16	17.8	*Pinus. patula*	1111	1045
B19	16	31.4	*Pinus. patula*	1111	701

Selection of Sirex noctilio infested compartments

In order to prevent statistical bias, pine compartments (n= 6) with the same age and species were selected from the study area (Table 1), thus reducing the effects of structural parameters on the spatial resolution analysis (Hyppanen 1996). For our purposes, additional localized sub samples (50 m x 50 m grids) were then generated over the selected *Pinus patula* compartments to provide a more representative sample (n= 308) that could be used for further analysis. Previous field visits to the plantation have shown that localized samples consisting of 50 m x 50 m grids are adequate to capture *S.noctilio* infestations. Additionally, studies examining the effects of spatial resolutions on vegetation mapping have also adopted a localized sub sample approach in an effort to provide a more representative sample size (Muwira, 2003; Colombo et al., 2004).

Description of image data

High resolution (0.5 m) image data was acquired on the 1 January 2006 by Land Resources International (LRI) Inc, Pietermaritzburg (South Africa) with their manufactured LrEye aerial imaging system. The LrEye sensor is composed of a series of four monochrome Sony cameras. Each camera collects data for one of the bands shown in Table 2. The resulting four bands are registered to form an image with four co-registered bands that are then referenced to the Transverse Mercator projection (Hartebeesthoek, central meridian: 29).

Table 2: Spectral and spatial range of the LrEye sensor

Band	Colour	Spectral range (nm)	Spatial resolution (m)
1	Blue (B)	450 to 480	0.5
2	Green (G)	550 to 580	0.5
3	Red (R)	650 to 680	0.5
4	Near Infrared (NIR)	850 to 900	0.5

Image processing and analysis

A number of vegetation indices (VI) have been successfully used to assess the changes in reflectance due to the declining health status of the trees (Vogelmann, 1990; Collins et al., 1996; Coops et al,. 2004; Leckie et al., 2004). Additionally, the advantage of using VI includes the removal of variability caused by canopy geometry, soil background, sunview angles and atmospheric conditions (Gilabert et al., 2002). In this study, the normalized difference vegetation index (NDVI) was used to determine *S.noctilio* infestation levels present within the study area. Investigators have shown that NDVI calculated from high spatial resolution (0.5 m) image data can successfully (87% classification accuracies) detect *S.noctilio* infestations (Ismail et al., 2006). In this study NDVI was derived from the high resolution image data (0.5 m) using equation (1) and rescaled to the range of 0 to 255 in order to facilitate data handling in the image processing software.

$$\frac{\lambda_1 - \lambda_2}{\lambda_1 - \lambda_2} \quad \text{(Rouse et al, 1973; Jackson, 1983)} \qquad (1)$$

Where: λ_1 , near infrared band (850 nm to 900 nm)

λ_2 , red band (650 nm to 680 nm)

To obtain the training signatures, six localized sub samples were randomly selected from the pine compartments shown in Table 1. Tree crowns located within each sub sample were manually identified on the 0.5 m image data and subsequently located in the field using a global positioning system (GPS). In total, 111 trees were visually assessed for *S.noctilio* red stage of attack. To prevent errors of commission, trees identified as red stage trees (those having a reddish brown canopy) were destructively sampled to check for the presence of *S.noctilio* larvae. Results indicated that all trees identified as red stage trees were positive for *S.noctilio* infestations.

Using the training signature obtained from the study area, the NDVI image was then classified into binary classes of red stage pixels and healthy pixels by means of a Gaussian maximum likelihood (GML) classifier (Erdas, 2004). GML classifier was used because it is relatively convenient to implement and more robust than other classification rules since it utilizes variances and covariances of training statistics as opposed to simpler statistics (Chen et al., 2004). Next, using the binary image, infestation levels (%) for the study area were calculated as the ratio of red stage pixels compared to the total number of pixels for each sub sample (n = 308) generated over the study area. These sub samples provided us with variable infestation levels (%) for which we would then examine the effects of spatial resolution.

Minimum variance

The method for calculating the minimum variance for each localized sub sample is relatively straightforward and is easily implemented in any image processing software. Firstly, to simulate variable spatial resolutions, the binary image data (0.5 m) as determined by the GML was successively resampled to coarser resolutions. The process involves calculating the average pixel value using odd sized n x n windows of increasing dimensions (Table 3). According to (Marceau et al., 1994) this averaging method is regarded as an efficient and simple way to represent the physical aggregation process of a sensor's instantaneous field of view (IFOV). Additionally, the nearest neighbour and cubic convolution algorithms used for resampling data, induce sharpening or smoothing effects that influences the analytical process (Bian et al., 1999)

Table 3: Window sizes used during the resampling process.

Window Size	Spatial Resolution (meters)
3 x 3	1.5
5 x 5	2.5
7 x 7	3.5
9 x 9	4.5
11 x 11	5.5
13 x 13	6.5
15 x 15	7.5

Next, the variance (equation 2) at each sub sample (n = 308) was calculated for all resampled spatial resolutions (binary images consisting of red stage pixels and healthy pixels). A similar process was adopted by (Colombo et al. 2004) who used the semivariance of binary images (forest and non forest pixels) to determine an appropriate spatial resolution fo- monitoring tropical forest cover.

$$Variance = \frac{\sum (x_{ij} - M^{8})^2}{n10^1} \qquad (2)$$

$$Mean = \frac{\sum x_{ij}}{n} \qquad (3)$$

Where: x_{ij} = DN value of pixel (i, j)

n = Number of pixels in a window

M = Mean of the moving window

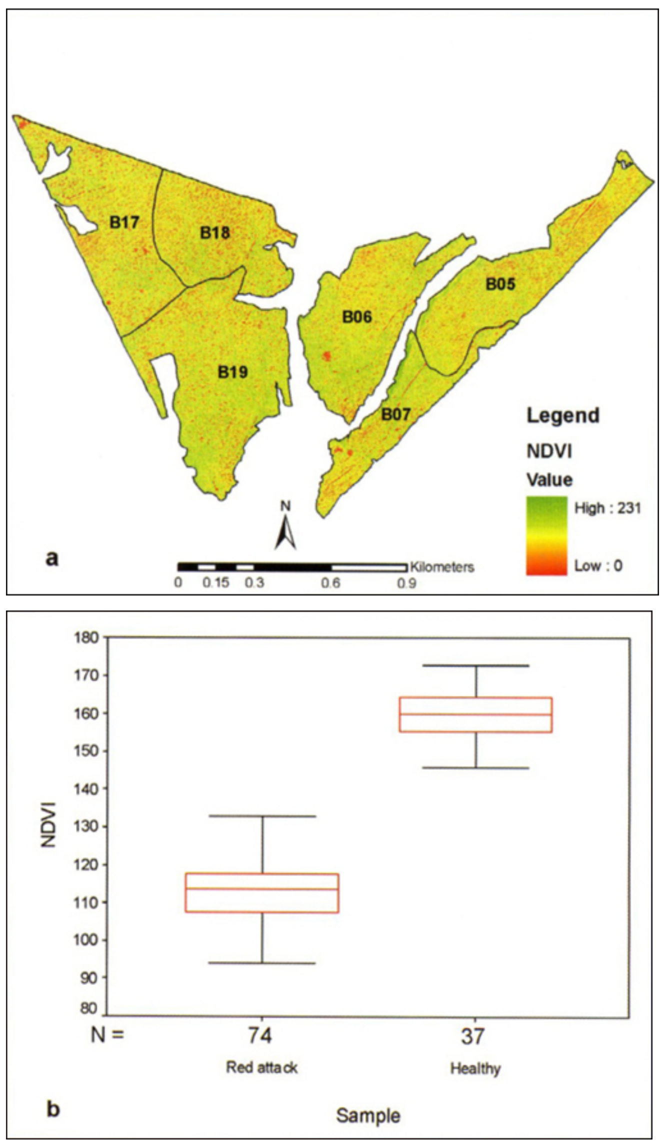
Finally, the spatial resolution at which each sub sample reaches a minimum variance was observed and tabulated. This spatial resolution was then averaged for each unique infestation level present in the study area and the resulting spatial resolution was defined as the 'optimal' spatial resolution. However, according to (Atkinson, 1997), where the objective is to map the spatial variation of interest, the spatial resolution chosen should not be the spatial resolution defined in this study as 'optimal'. It was suggested that the spatial resolution used should be much finer than the calculated 'optimal' spatial resolution because the objective for mapping is not to maximize the amount of information per pixel but to ensure that there is sufficient information of interest to be sampled. According to sampling theorems, to effectively sample objects, one must sample at least at one-half the width of the object under investigation (McGrew et al., 2000).Therefore, for our purpose, a pixel smaller than or equal to half the 'optimal' spatial resolution would be an appropriate resolution for the detection and monitoring of *S.noctilio* infestations.

Results

Classification results

Figure 2 (a) shows the derived NDVI image for the study area. The original NDVI values (-1 to 1) were rescaled to the range of 0 to 255 (Erdas, 2004). The lower limits of the range indicate the absence of vegetation while the upper limits indicate very healthy vegetation. The derived NDVI values for the study area had a lower limit of 0 and an upper limit of 231. Box plots in figure 2 (b) show the spread of NDVI values for the healthy (n = 37) and red stage trees (n = 74). The mean differences between the two groups were tested using a t test and the normality of the data was assessed using a Kolomogrov-Sminov test ($p > 0.05$). The results from the test indicated that NDVI values significantly differ between the red stage and health trees ($p > 0.05$). Consequently, the training samples (n = 111) were then used to classify the NDVI image into binary classes of healthy and red stage pixels.

Figure 2: NDVI values derived from high spatial resolution (0.5 m) image data. (a) Shows the spatial pattern of NDVI values in the study area. (b) Shows the spread of NDVI values for healthy (mean = 160; standard deviation = 7.1) and red attack trees (mean = 113; standard deviation = 9.3).



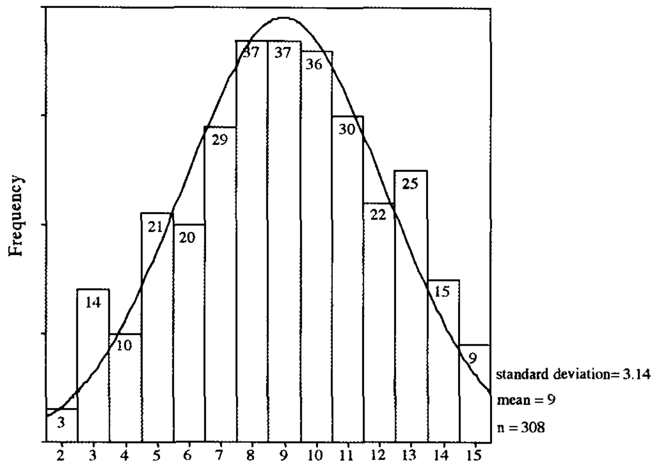
Infestation levels, calculated as the ratio of red attack pixels compared to the total amount of pixels revealed that there is 19.5 % infestation at a plantation scale. Infestation levels calculated at a compartment level (n = 6) are shown in Table 4. For comparative purposes, independent forest health enumerations (field based) are provided for the selected compartments (Croft, 2006). A Mann-Whitney U Test revealed that there was no significant difference ($p < 0.05$) between the field based and the binary infestation levels. However, in order to determine an appropriate pixel size to capture the spatial variability of *S.noctilio* infestations, the localized sub samples (50 m x 50 m grids) provided a more representative sample of infestation levels (n = 308) as opposed to infestations levels at a compartment level (n = 6).

Table 4: Comparison of *S.noctilio* infestation levels at a compartment scale.

Compartment	Sirex Infestation (%) (NDVI)	Sirex Infestation (%) (Field based results)
B05	24	16
B06	17	17
B07	4	3
B17	25	26
B18	26	35
B19	21	21

Based on the existing damage classes used by foresters, infestation levels were categorized into low (1-5%), medium (6-10%), high (11-15%) and severe (>16%) classes (Croft, 2006). Figure 3 shows the variability of infestation levels throughout the study area as calculated for the sub samples. There is a predominately medium to high infestation levels with 15.43% of the grid cells have a low infestation levels while 51.77% have a medium infestation level and 32.80% have a high infestation level. As expected there are no sub samples with severe infestations levels (>16%). Localized areas having severe infestation levels are easily identifiable by foresters and measures such as clear felling operations would have been implemented in order to salvage "utilizable" red stage trees and to prevent *S.noctilio* from spreading to other compartments in the plantation.

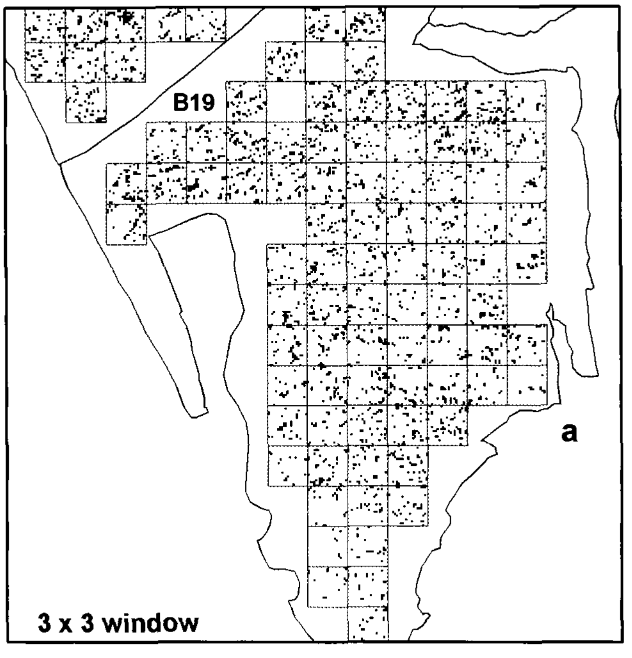
Figure 3: Histogram showing the infestation levels within the study area (50m x 50m grid)

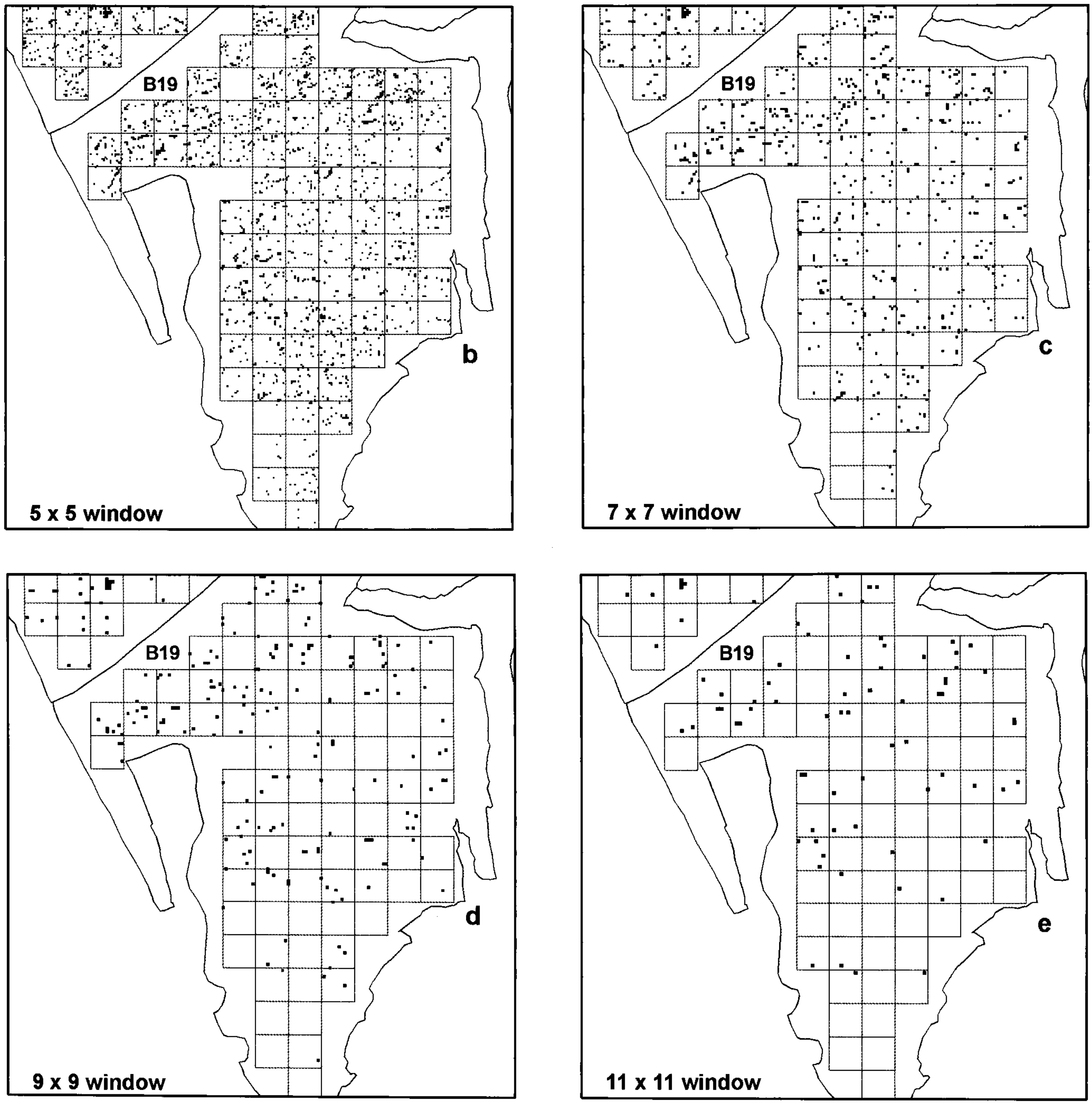


Minimal variance

Figure 4 shows the process of resampling the original 0.5 m binary image (i.e. healthy and red stage pixels) by using odd sized windows (3 x 3, 5 x 5, 7 x 7 and so on). One of the effects of the resampling process is that the number of pixels decreases as the resolution becomes coarser (Woodcock et al., 1987). Especially noticeable is that, grids cells with lower infestation levels (1-5%) result in a greater loss of pixels during the resampling process. Therefore, there are a limited number of times that the image data can be resampled and still have a reasonable number of pixels to estimate variance.

Figure 4: An example of the resampled binary images that were used to determine the minimal variance. The spatial pattern *S.noctilio* infestations for compartment B19 are shown at 1.5 m (a), 2.5 m (b), 3.5 m (c), 4.5 m (d), 6.5 m (e) and 7.5 m (f) spatial resolutions.





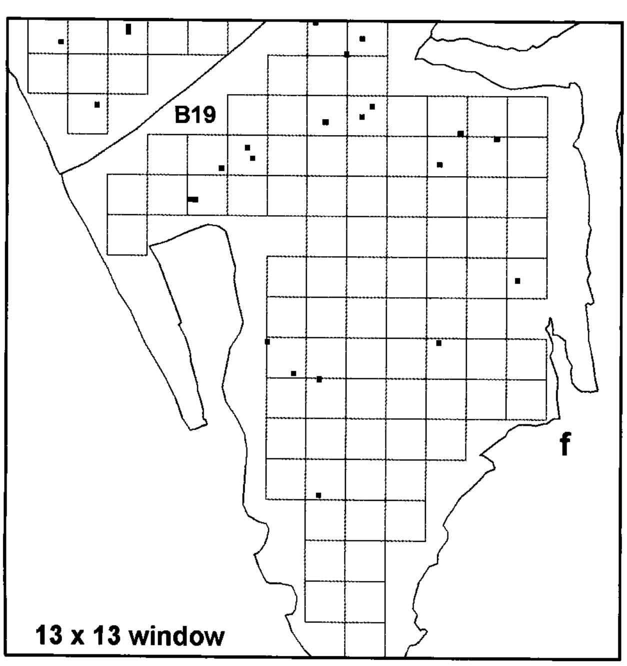
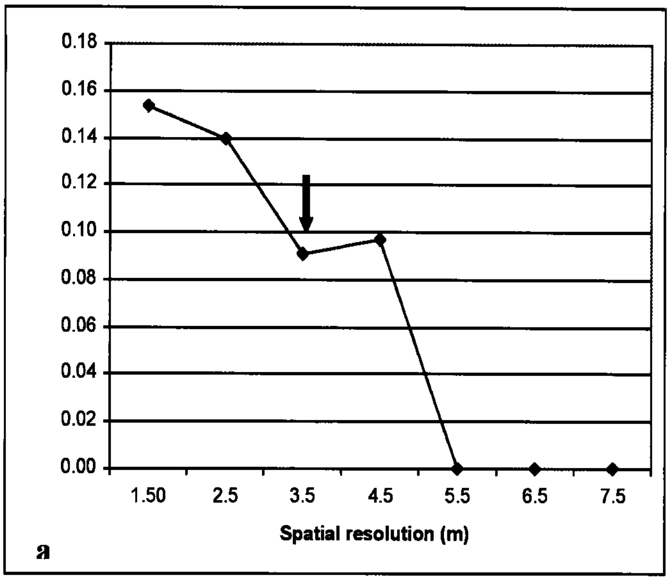
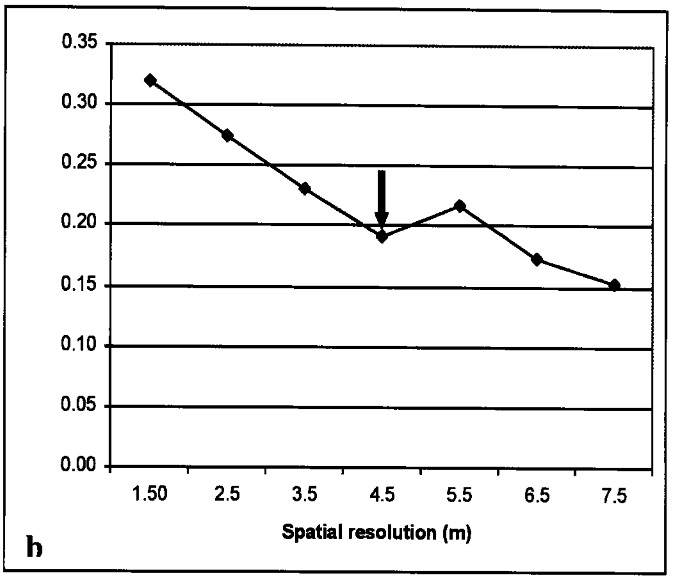


Figure 5 shows the variance plotted as a function of the resampled spatial resolutions. Two dominant trends are observed from the data, firstly, for low to medium infestation levels (1-10%) the variance is relatively high at 1.5 m, decreases to reach a minimum at an intermediate resolution and reaches a value of zero in the coarser resolutions (Figure 5a). As mentioned earlier, the zero variance values obtained at coarser resolutions are due to the resampling process. Secondly, for the high infestation levels (11-15%) the variance is relatively high at 1.5 m, decreases towards the intermediate resolution and stabilizes in the coarser resolutions (Figure 5b). In both cases, the minimum variance is observed when the variance of the pixels for each sub sample is at the lowest level. This drop in variance (minimal variance) is then used as a measure of the 'optimal' resolution that takes into account the inherent spatial properties of varying infestation levels.

Figure 5: Graphs indicating trends of the calculated minimal variance. The spatial resolution at which each sub sample reaches a minimum variance is shown with an arrow. Figure 5a shows trends prevalent in low to medium infestation levels (1-10%) while Figure 5b shows the trend in variance for high infestation levels.





The 'optimal' spatial resolutions as determined by minimum variance was then averaged for each unique infestation level (n = 14) and the resulting spatial resolutions are shown in Table 5. Since our aim was to define an appropriate pixel size to capture the spatial variability of *S.noctilio* infestation and following the sampling theorem (McGrew et al., 2000), results show that the appropriate resolutions for low to medium infestation levels range between 1.75 m and 1.93 m, while the appropriate resolution for higher infestation levels (11-15%) are between 1.99 m and 2.31 m. Furthermore, correlation analysis was undertaken to examine the relationship between the appropriate spatial resolutions and *S.noctilio* infestation levels. The coefficient of determination ($r^2 = 0.87$, $p < 0.001$) indicated that there is a strong correlation between the appropriate spatial resolutions and *S.noctilio* infestation levels. Results indicate that areas with high infestations levels can be detected using coarser resolution remotely sensed data and areas with low infestation levels can be detected using finer remotely sensed data.

Table 5: Infestation levels and spatial resolution

Infestation Rate (%)	Resolution (Minimum Variance)	Infestation Level	Resolution (SamplingTheorem) (m)
2	3.50	Low	1.75
3	3.50	Low	1.75
4	3.50	Low	1.75
5	3.64	Low	1.82
6	3.50	Medium	1.75
7	3.64	Medium	1.82
8	3.64	Medium	1.82
9	3.92	Medium	1.96
10	3.86	Medium	1.93
11	3.98	High	1.99
12	3.95	High	1.98
13	4.18	High	2.09
14	4.37	High	2.19
15	4.61	High	2.31

Discussion

For remote sensing technologies to be widely accepted by forest managers and for these tools to be used on an operational basis, methods must allow for the efficient and cost effective mapping of *S.noctilio* infestations. In this context, minimal variance calculated for localized sub samples has proven to be a useful tool in determining an appropriate spatial resolution for the detection and monitoring of *S.noctilio* infestation levels. Although the range of appropriate spatial resolutions is narrow (<0.5), there would be a significant reduction in the cost of acquiring image data, since costs are primarily dependant on pixel size. The results obtained are consistent with the hypothesis, that each object mapped using remotely sensed data has a scale or a narrow range of scales associated with it, which provides its best representation (Marceau et al., 1994).

The results from this study provide the following guidelines: (i), for areas that have known *S.noctilio* infestations (medium to high infestation levels) pixels sizes between 1.75 m to 2.3 m would be sufficiently detailed to capture infestation rates, while (ii) newly colonized areas or areas susceptible to infestation (low infestation levels), a pixel size of 1.75 m would be appropriate. Using pixel sizes larger than 2.3 m may not provide adequate information for high infestation levels (11-15%), while using pixel sizes smaller than the 1.75 m for detecting low to medium infestation levels (1-10%) could mean an unnecessarily large volume and cost of data.

However, determining the appropriate resolution for an investigation is a function of the type of environment, the kind of information desired and the techniques used to extract the information (Chen et al. 2004, Garrigues et al. 2006). For example, optimal resolution studies have shown that using different vegetation indices produce different results (Menges et al., 2001, Rahman et al., 2003). According to Menges et al. (2001), these differences are related to the suppression or enhancement of certain features on the image. Furthermore, the inclusion or exclusion of certain wavelengths might have implications for users wishing to select an appropriate resolution (Atkinson et al., 2004).

To summarize, defining appropriate pixel for an application is complex task and depends mainly on the objectives of the study and the techniques used to retrieve the required information, firstly the pixel size should be large enough to be consistent with the object (tree crowns) targeted and fine enough to capture the spatial variability of the data and minimize intra-pixel variability. The appropriate pixel sizes proposed in this study provide an indication of the upper (2.3 m) and lower (1.75 m) limit of the appropriate pixel sizes that are suitable for detection and monitoring of *S.noctilio* infestations.

Summary and conclusions

In this study, the effects of spatial resolution on detecting *Sirex noctilio* infestation levels were examined at a sub sample level using classified NDVI images. This procedure allowed us to establish the appropriate spatial resolution guidelines necessary for the operational monitoring and detection of *S.noctilio*. The appropriate pixel size should be chosen between the upper and lower limits proposed in this study but additional factors such as economic and technical constraints should be considered. Some of the major findings from the study are as follows:

Minimum variance calculated for localized sub samples is a useful tool for identifying the appropriate spatial resolution needed for a particular investigation. When using a spectral classifier (for example, NDVI) to detect infestation levels, pixel sizes larger than 2.3 m will not provide adequate information for high infestation levels (11-15%), while using pixel sizes smaller than the 1.75 m for detecting low to medium infestation levels (1-10%) could mean an unnecessarily large volume and cost of data. Although the identified range of appropriate spatial resolutions is narrow (< 0.5 m), using the appropriate spatial resolutions as determined by this study would result in the reduced costs of future image data acquisitions.

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